Scalable Compact Models for Complex High-Speed Systems

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WMC: Advanced techniques for electromagnetic-based model generation

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Introduction

Scalable Macromodels

Numerical examples

- Data-driven PMOR
- Model-driven PMOR

Conclusions

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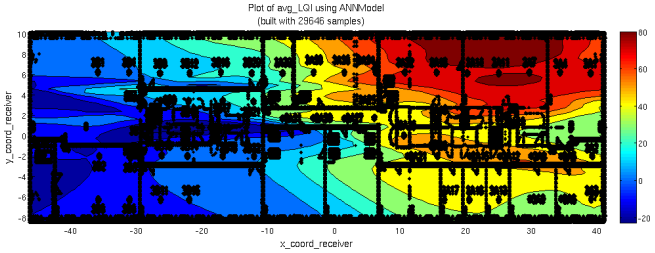
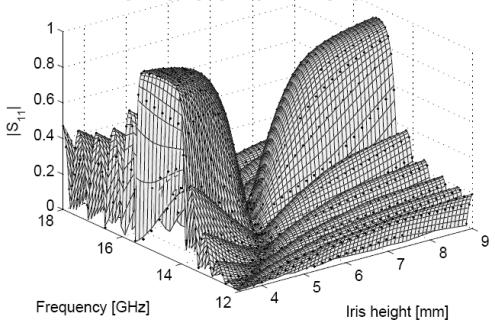
Introduction

telecom

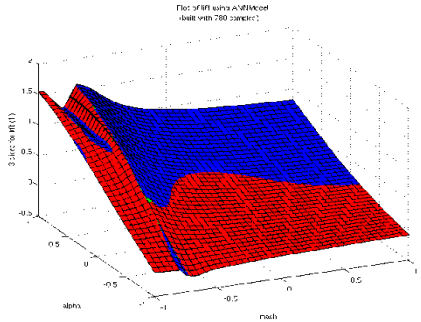


electronics



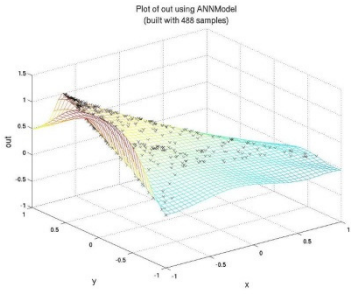
input → out = f(*in*) → output

fluid dynamics

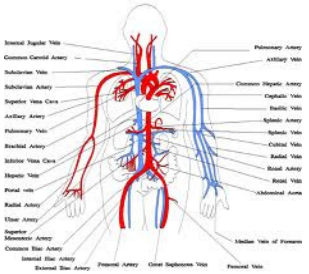


automotive

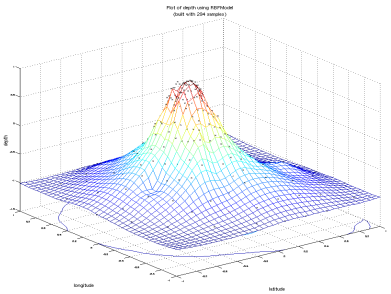
chemistry



biomodeling



geology



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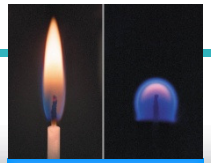
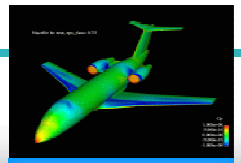
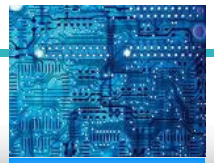




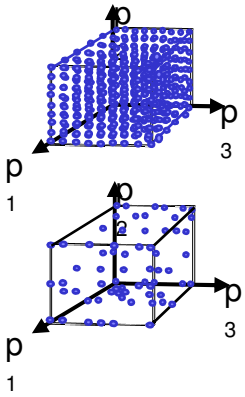

Automotive | Chemistry | Aerodynamics | Electronics | Metallurgy

Design variables → **Simulation Model** (Fluent®, HSPICE®, CST®, Comsol®, Abaqus®, ...) → **Response variables**

width, temperature, angle, frequency, ...

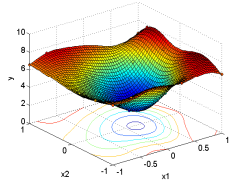
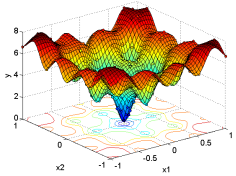
Costly

lift, S-parameters, pressure, stress, ...



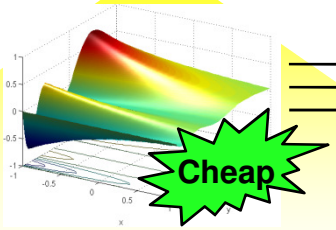
Configurable infrastructure

Adaptive Modeling

Distributed Computing

Design variables → **Response variables**



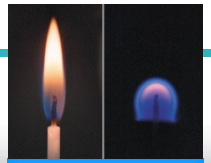
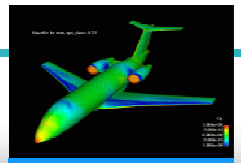
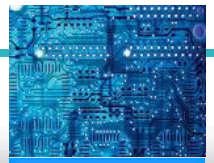
Cheap

Surrogate Model / Metamodel

Neural network, Kriging, SVM, rational function, spline,...

Prototyping | Optimization | Sensitivity Analysis | CAD/CAM/CAE Environment

Introduction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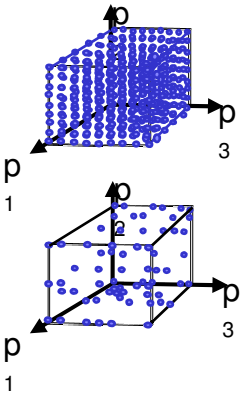

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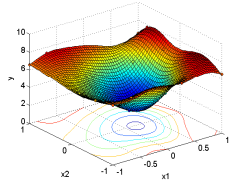
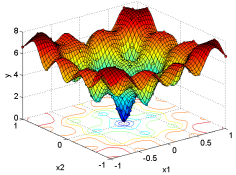

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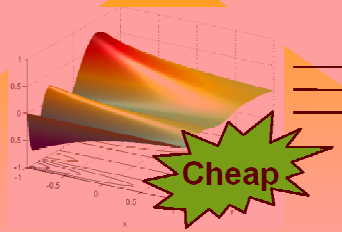

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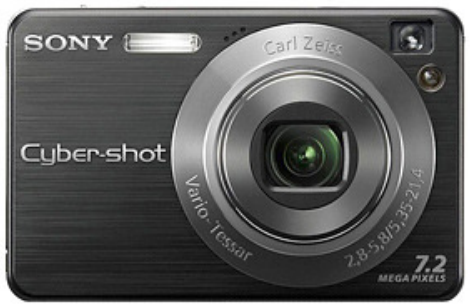

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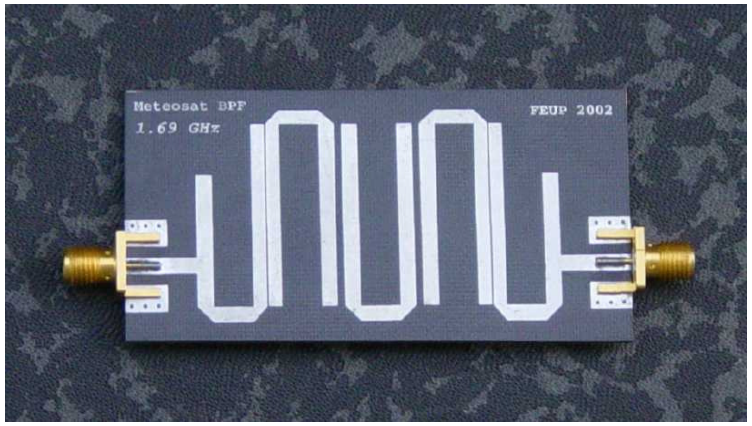
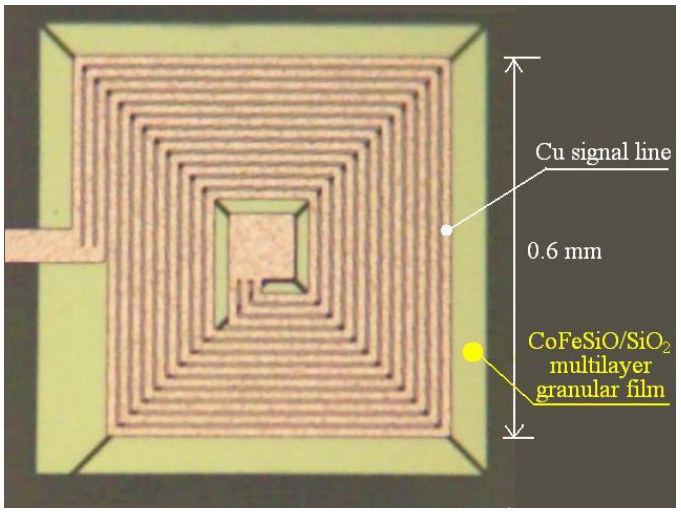




Introduction

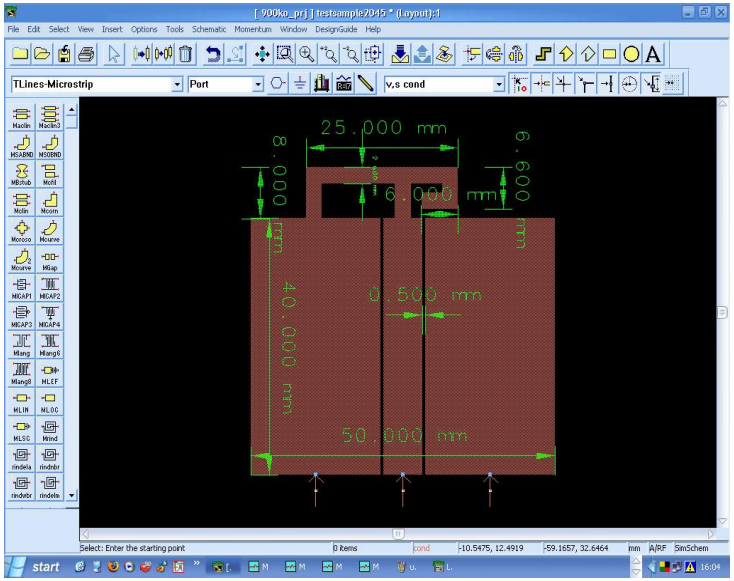
Design process

- several decisions
  - materials
  - geometrical dimensions
  - shape
  - constraints
    - space
    - cost
    - performance

Design process

Simulators

- implementation of models
- describe systems behavior
- help designers



Measurements

- post tuning
- verification
- help designers

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Scalable Macromodels

Numerical examples

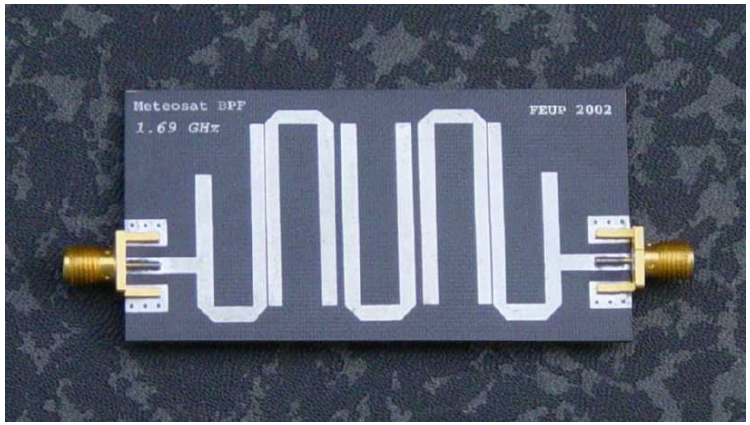
- **Data-driven PMOR**
- **Model-driven PMOR**

Conclusions

Scalable macromodels

A typical design process requires

- **Multiple simulations (measurements)**
  - **different design parameters values (e.g. layout features)**
  - **design space optimization**
  - **design space exploration**
  - **sensitivity analysis**



Scalable macromodels

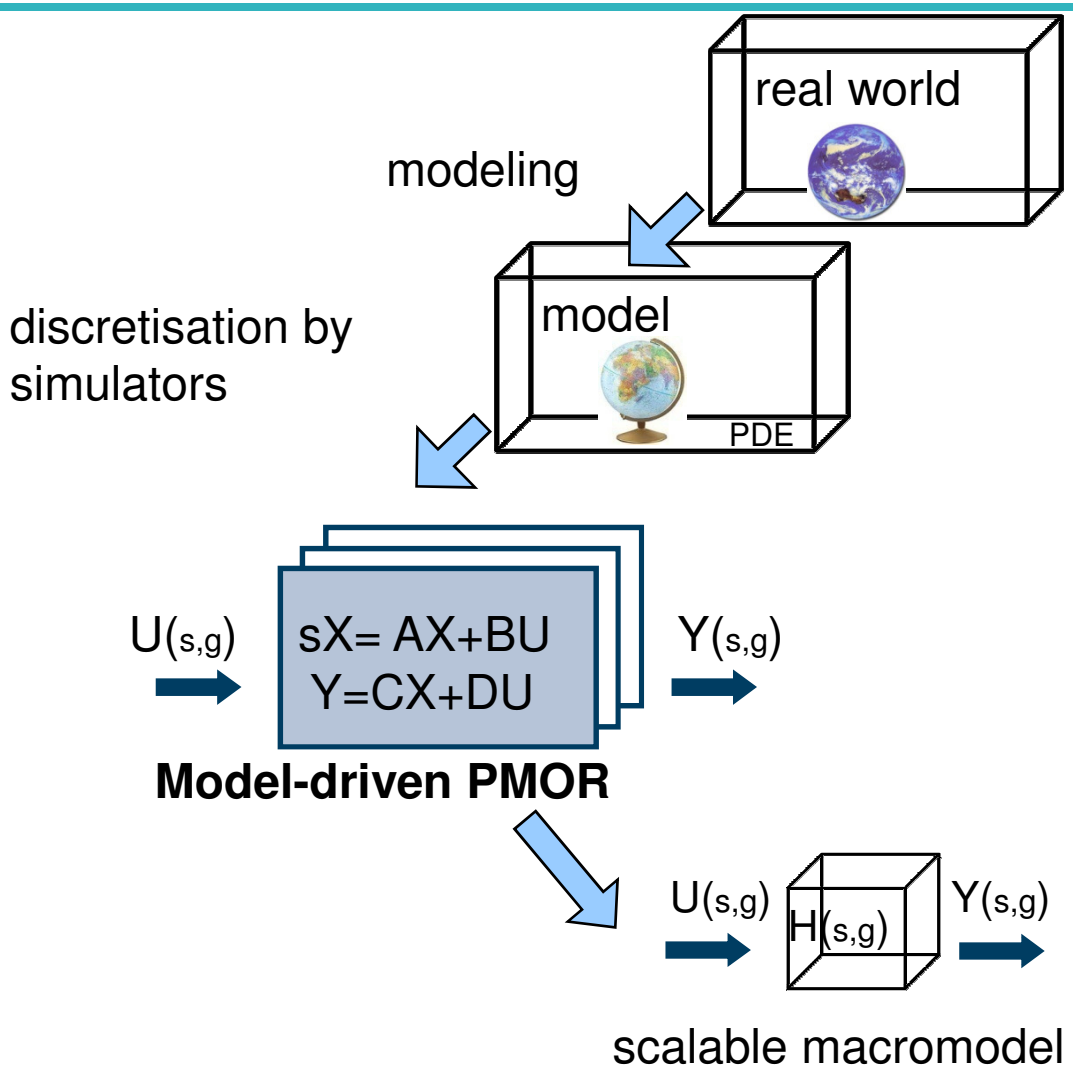
A typical design process requires

- **Multiple simulations (measurements)**
  - **computationally expensive (time and memory)**

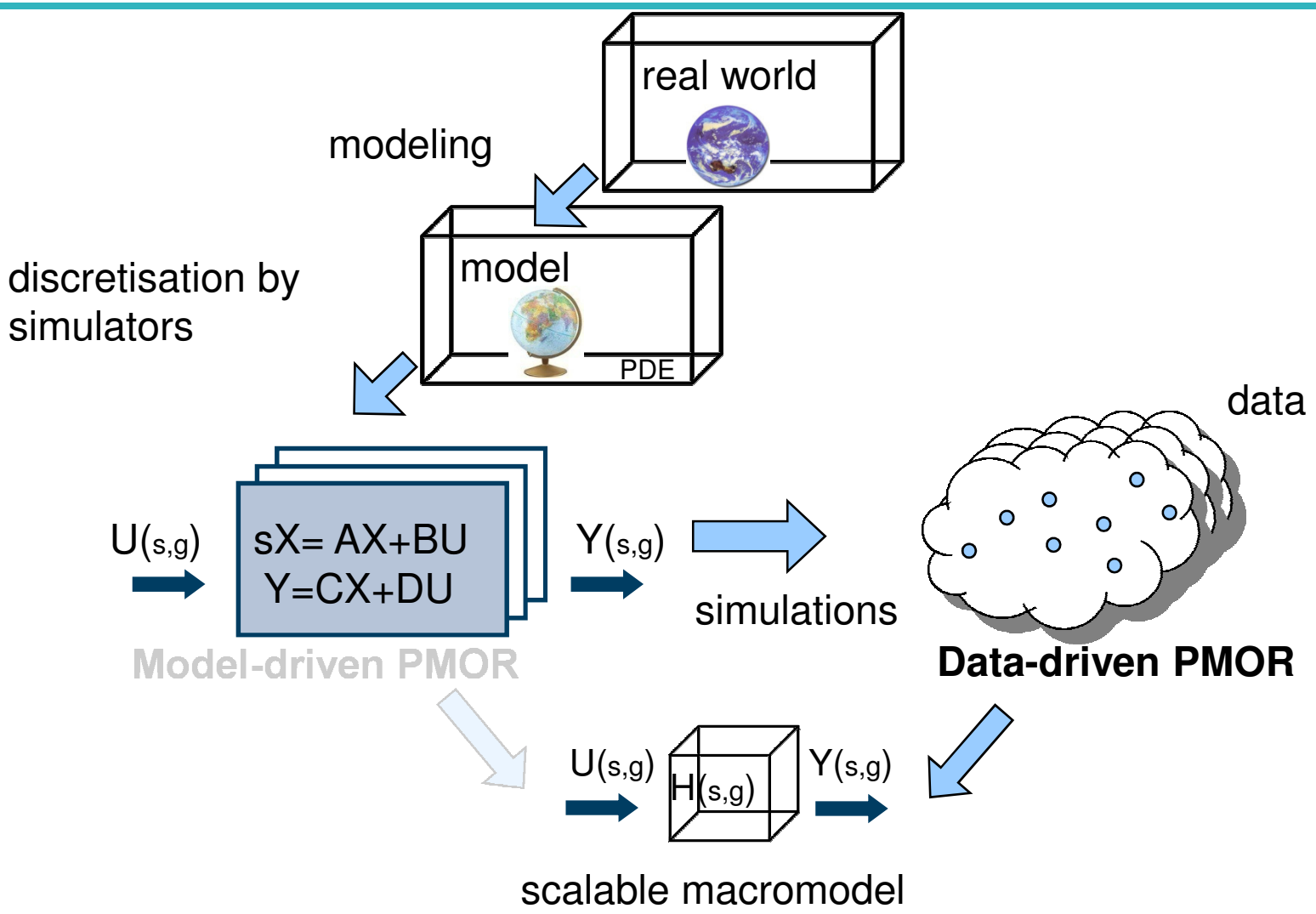
- **Can we do better?**

- **Yes**
  - **By scalable macromodels**

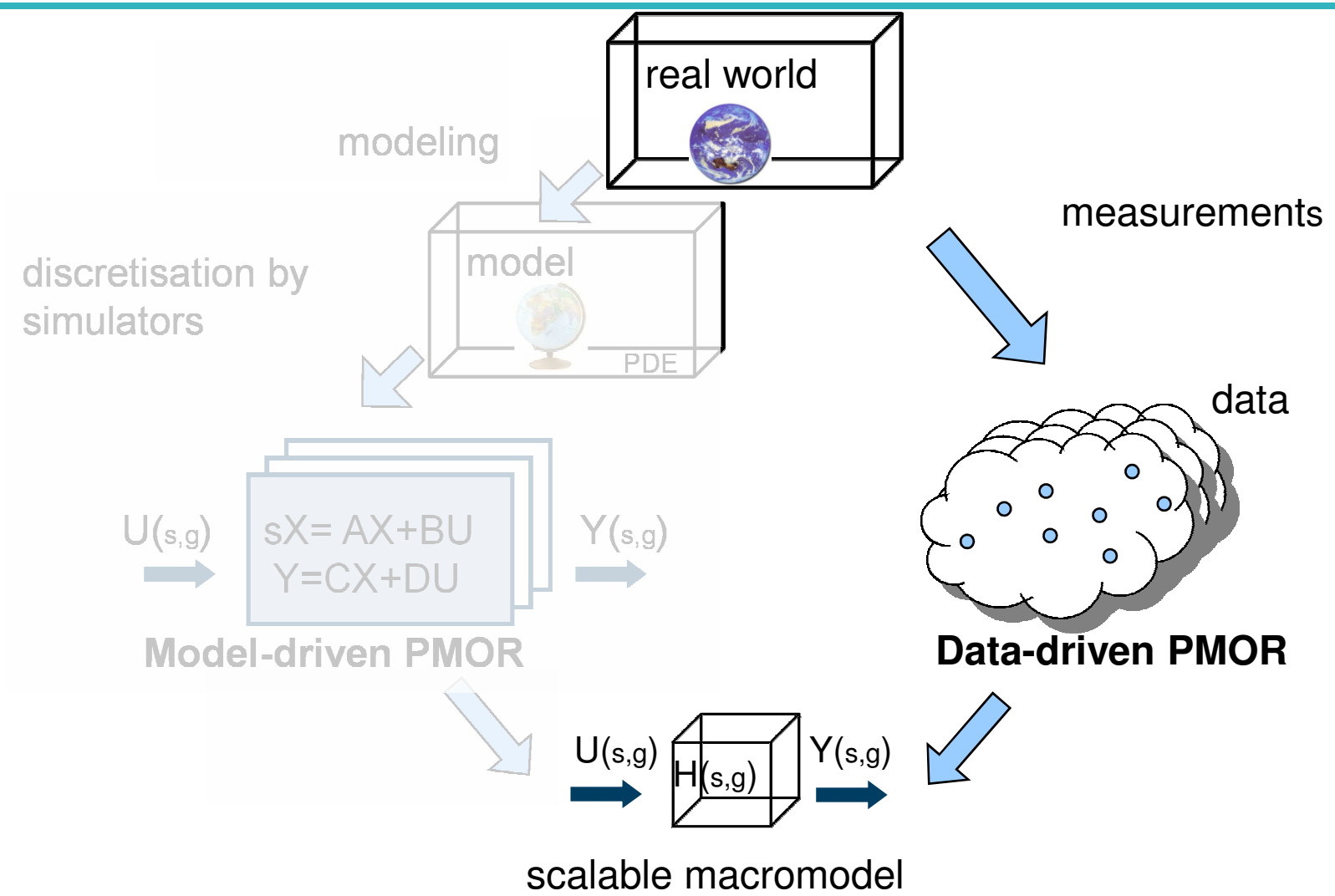
Scalable macromodels



Scalable macromodels



Scalable macromodels



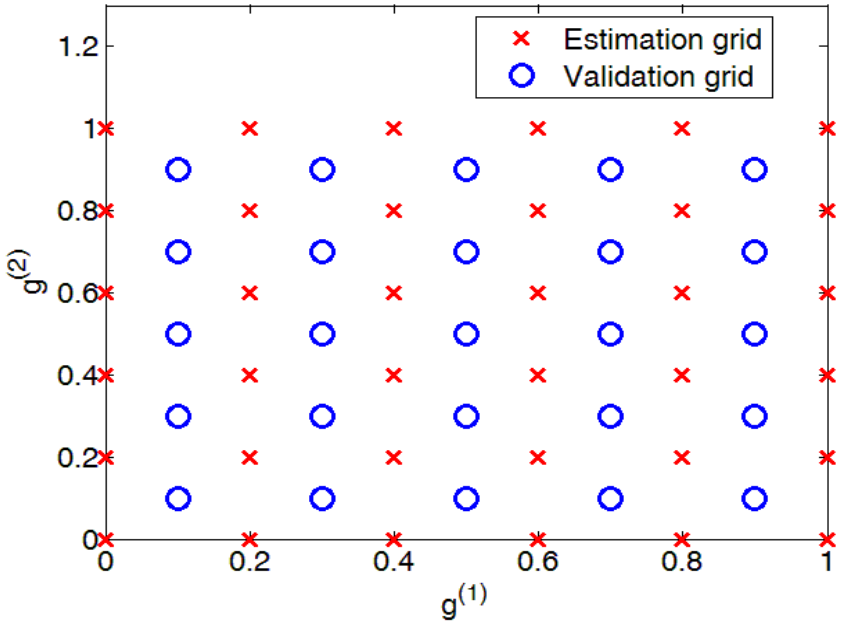
Scalable macromodels

PMOR concepts

Two design space grids are used in the modeling process

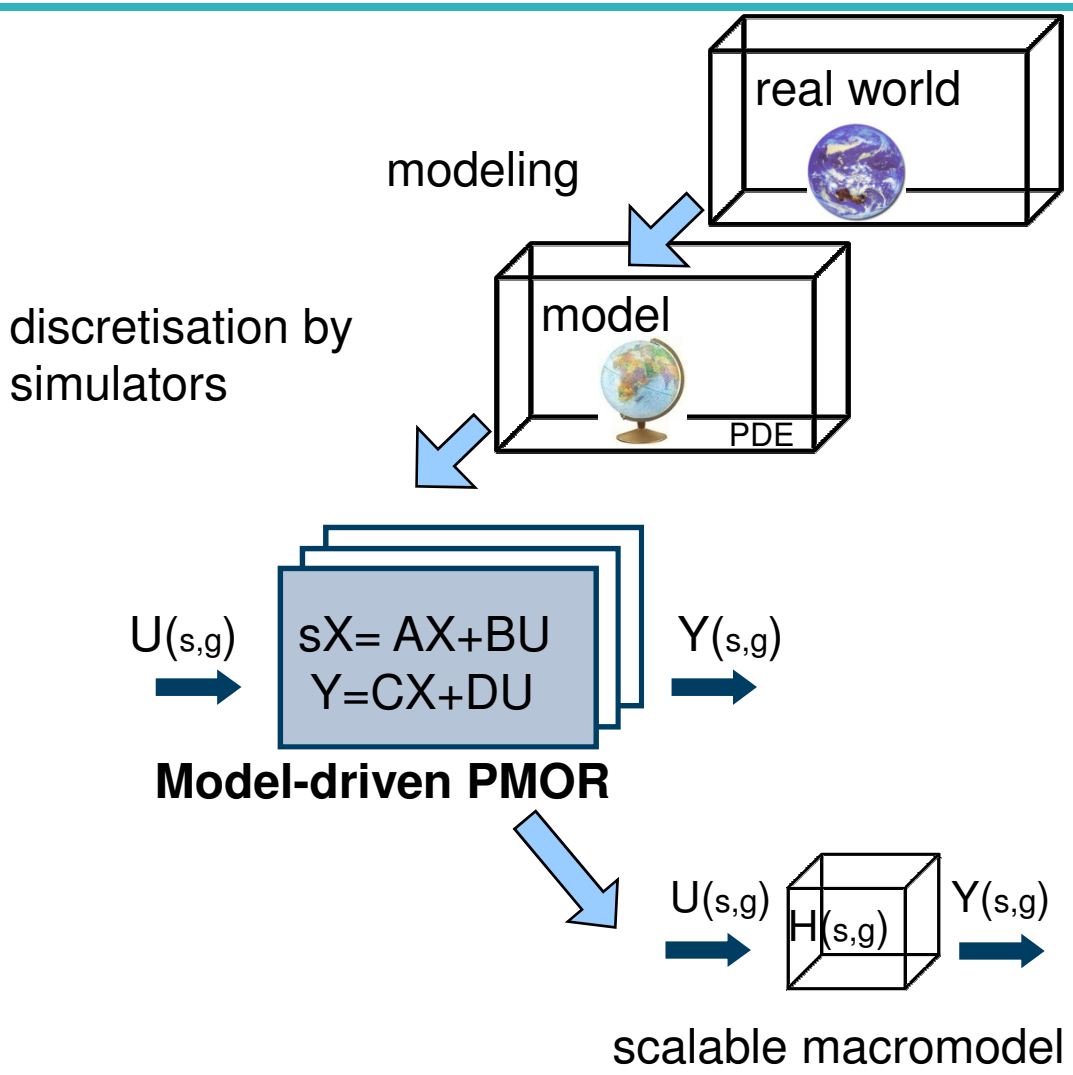
- **estimation grid**
- **validation grid**

Design space

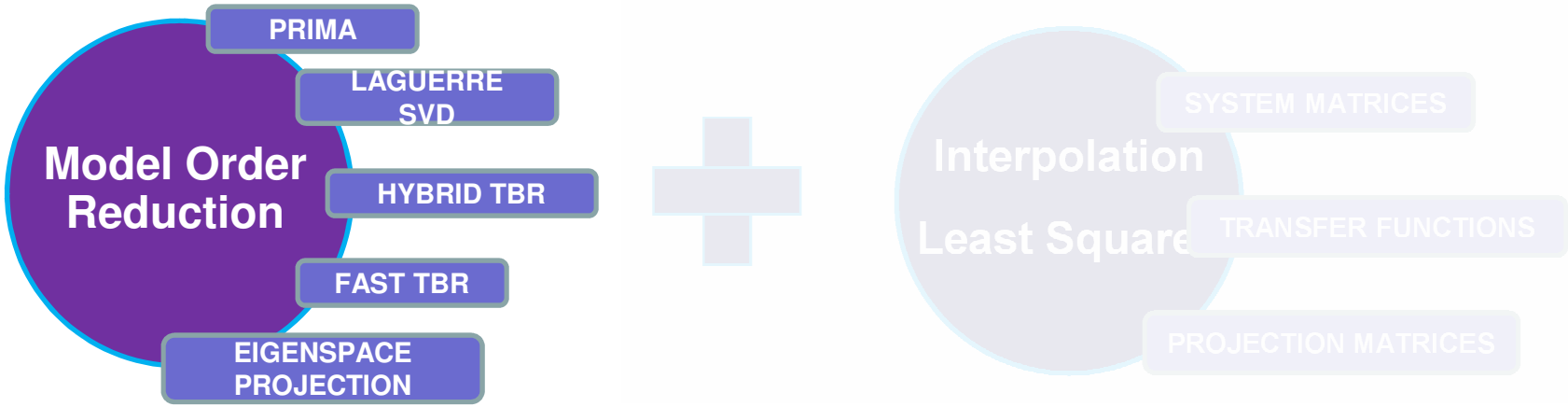


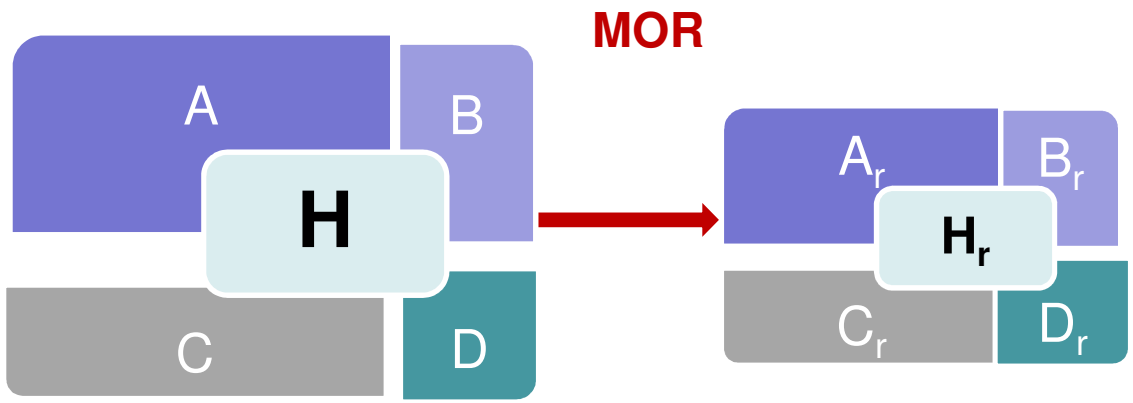
$$g = (g^{(n)})_{n=1}^{N}$$

Scalable macromodels



Model-driven PMOR





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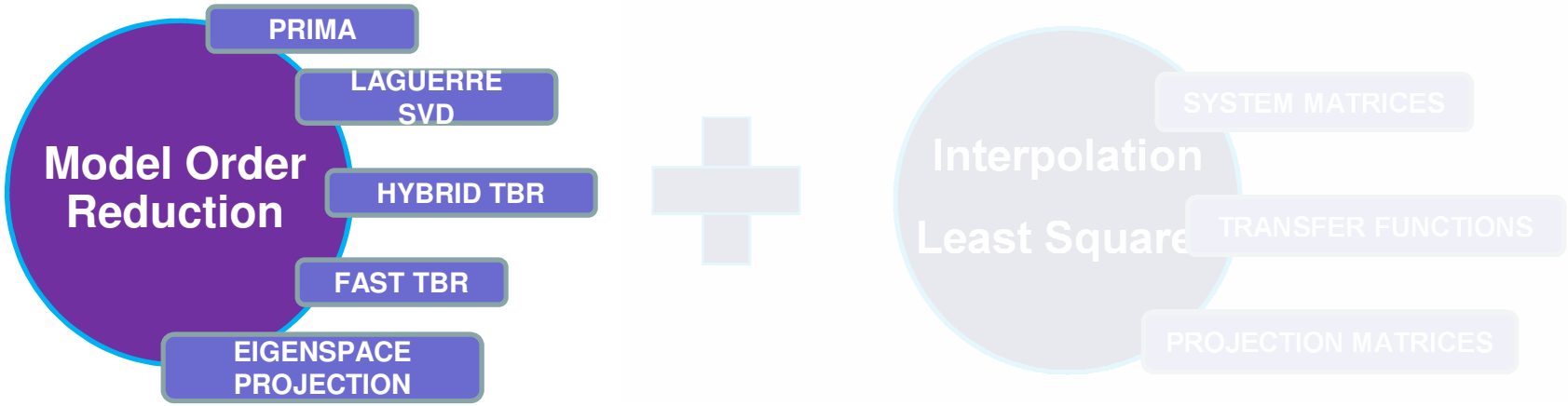

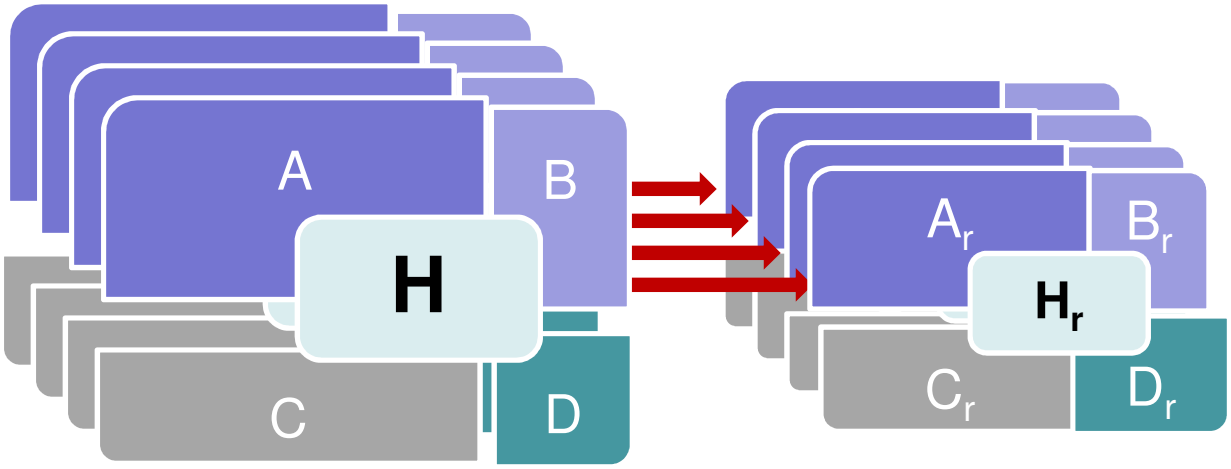

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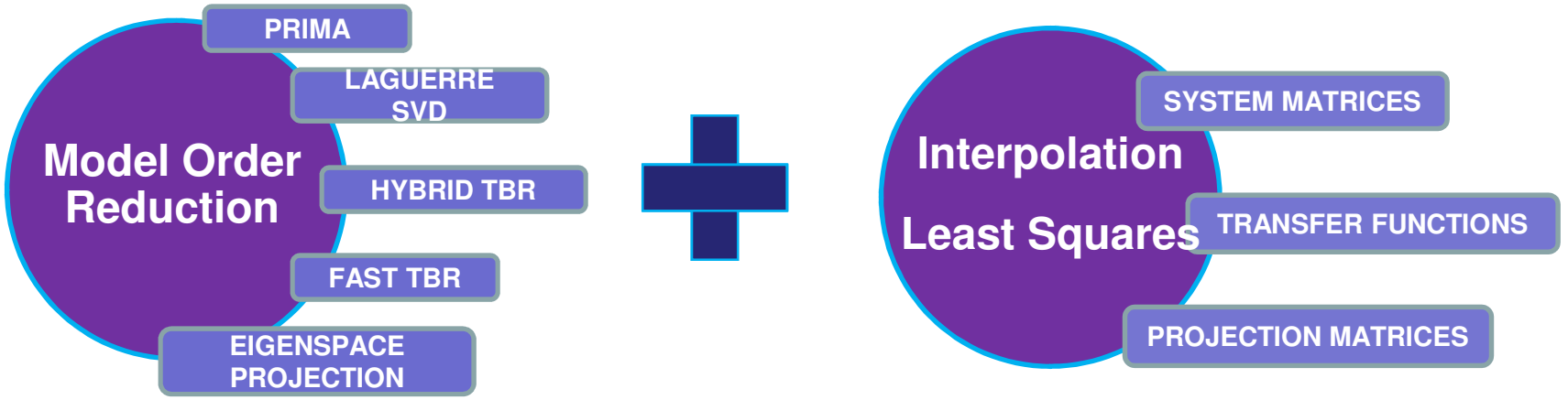
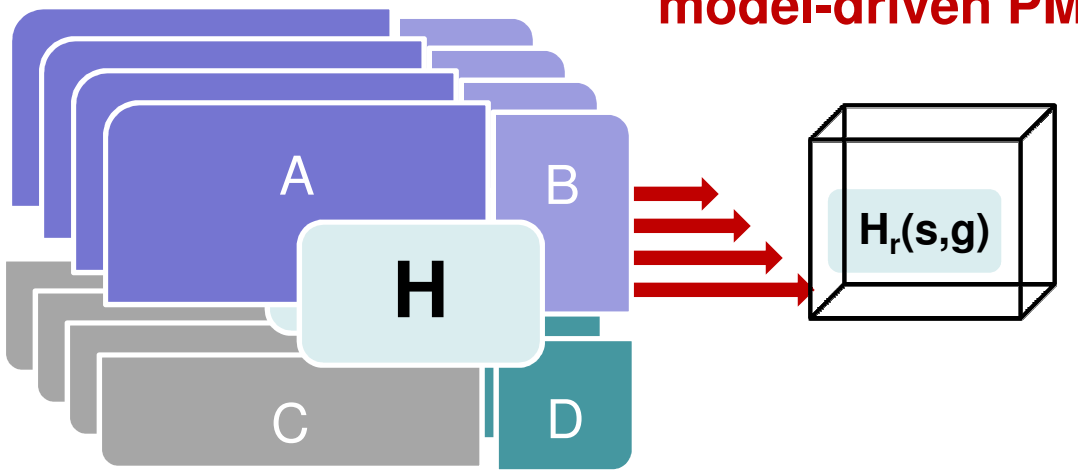
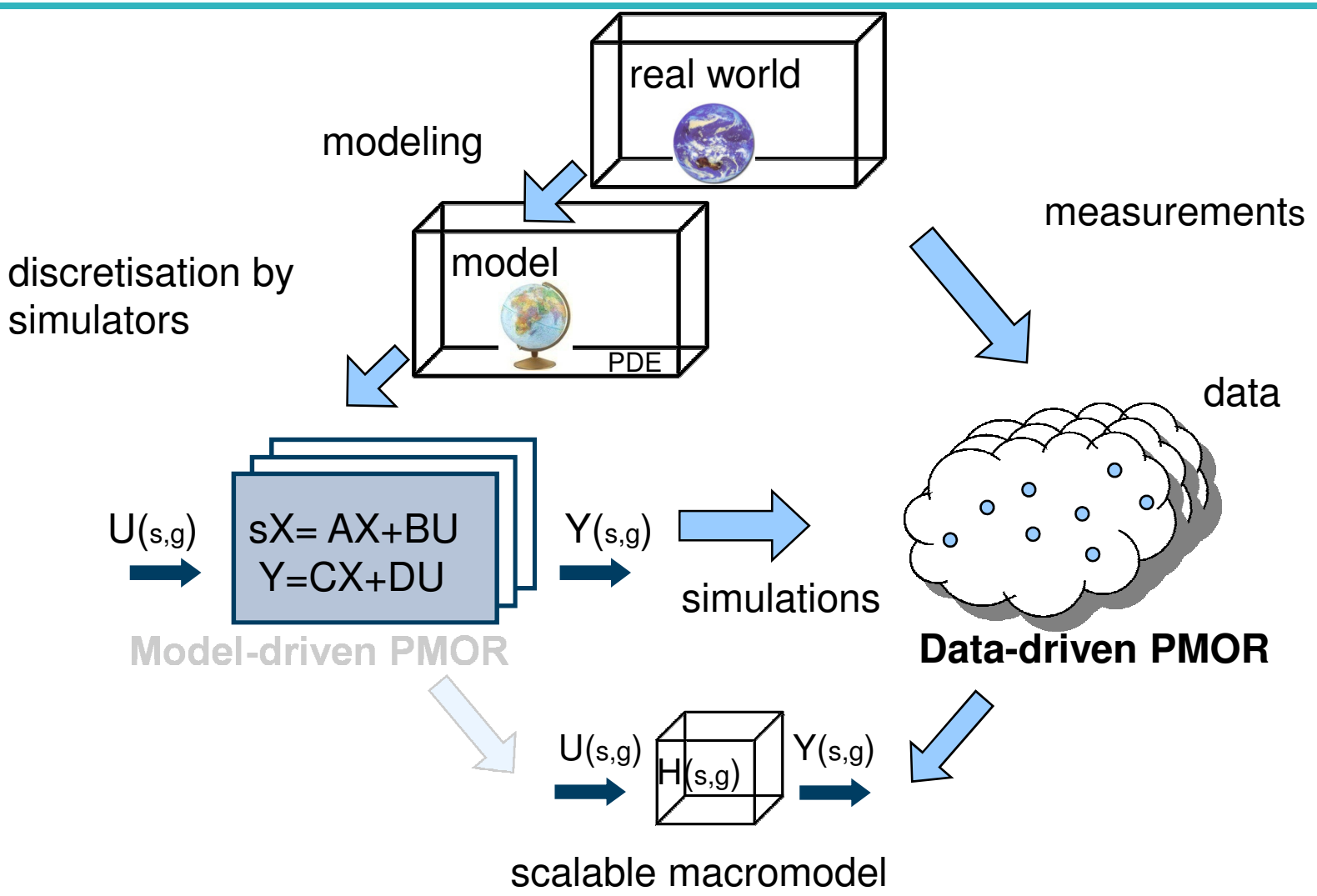


model-driven PMOR



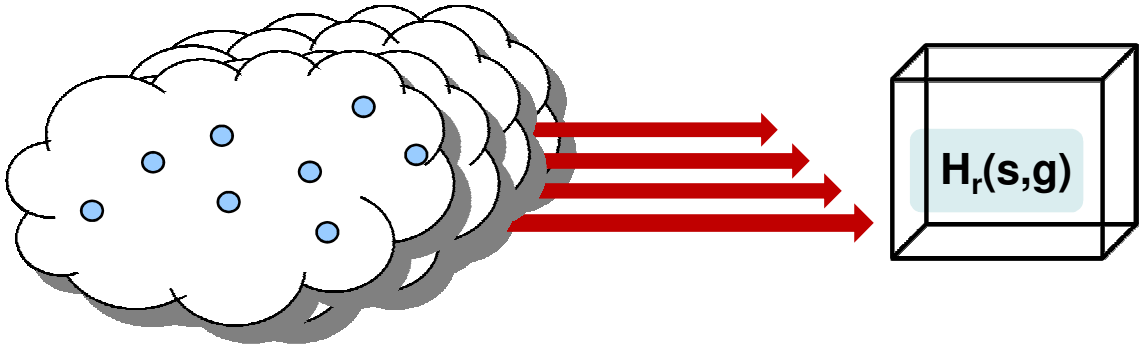
- accuracy
- efficiency
- stability guaranteed
- passivity guaranteed

Data-driven PMOR



Data-driven PMOR

data-driven PMOR

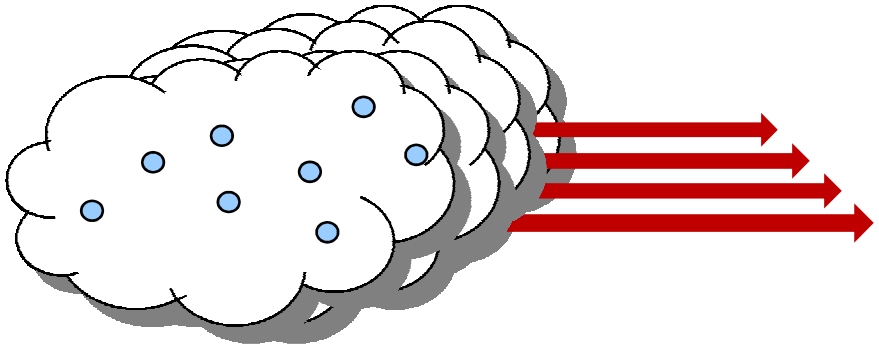


scattered data

- accuracy
- efficiency
- stability guaranteed
- passivity guaranteed

Data-driven PMOR

data-driven PMOR



scattered data

$$\mathbf{H}_r(s,\mathbf{g}) = \sum_{p=1}^{P} \frac{\mathbf{Q}(\mathbf{g})}{s - a_p(\mathbf{g})}$$

$$\mathbf{H}_r(s,\mathbf{g}) = \mathbf{C}(\mathbf{g})(s\mathbf{I} - \mathbf{A}(\mathbf{g}))^{-1}\mathbf{B}(\mathbf{g}) + \mathbf{D}(\mathbf{g})$$

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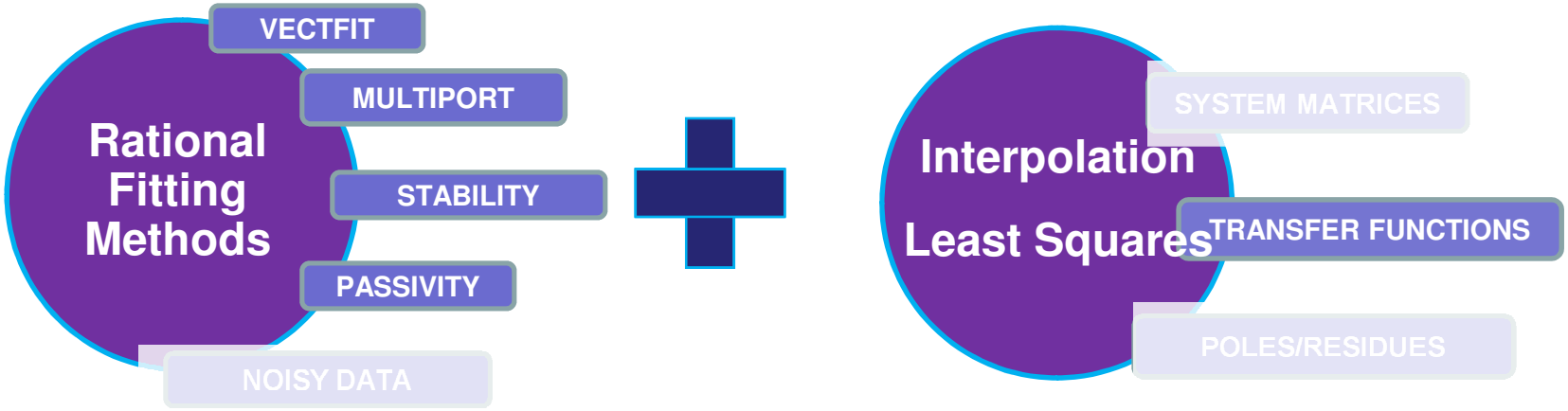

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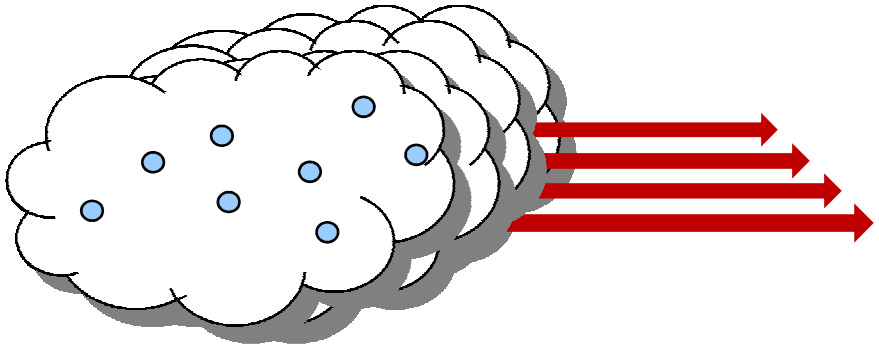

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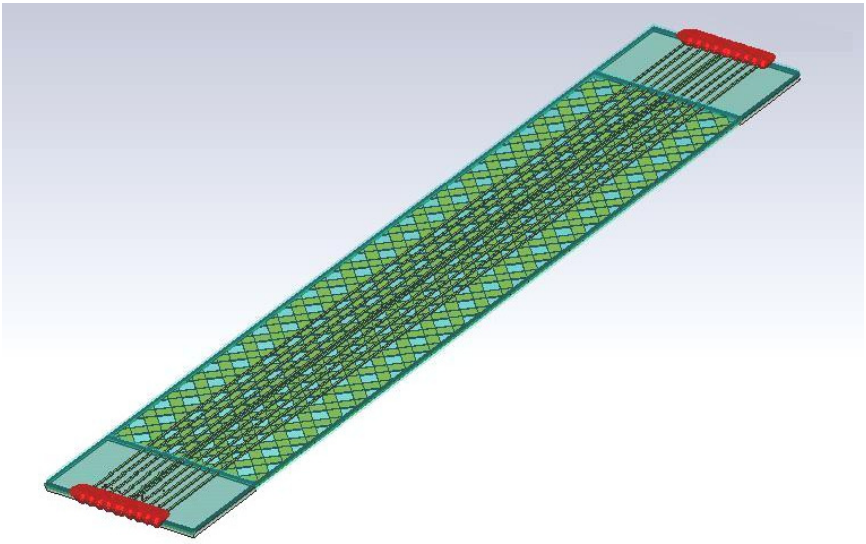
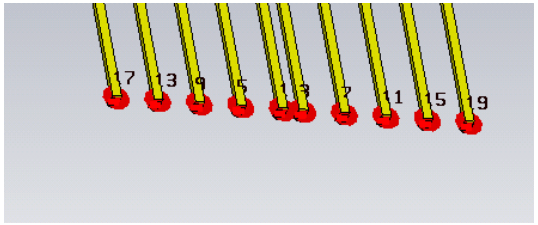
Data-driven PMOR example

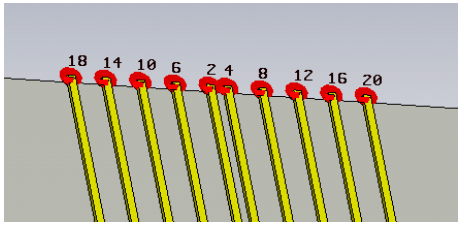
3D example: Interconnection structure

- **Mobile phone application**
- **10 lines (20 ports)**
- **etched ground plane**

Parameter	Min	Max
Frequency ($freq$)	0 Hz	20 GHz
Spacing (S)	25 μm	65 μm
Angle (α)	45°	65°





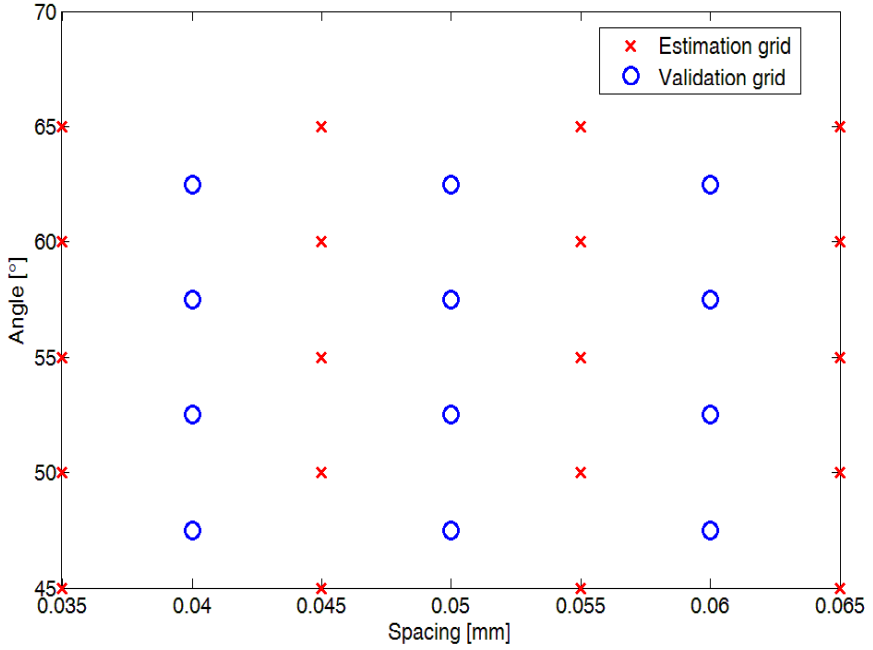


Data-driven PMOR example

- **CPU time model estimation**
- **CPU time model validation**

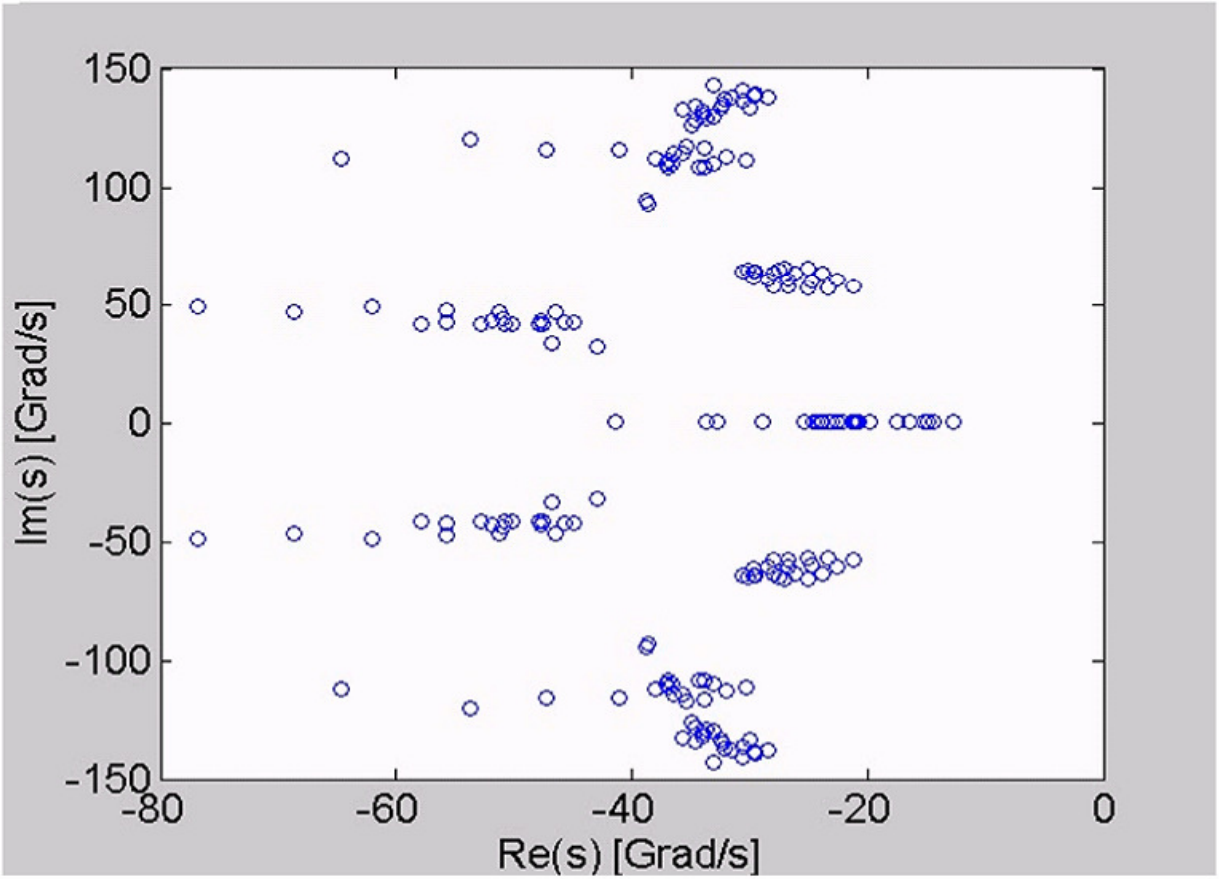
Step	CPU time
Estimation	10 h
Validation	6 h

Design space



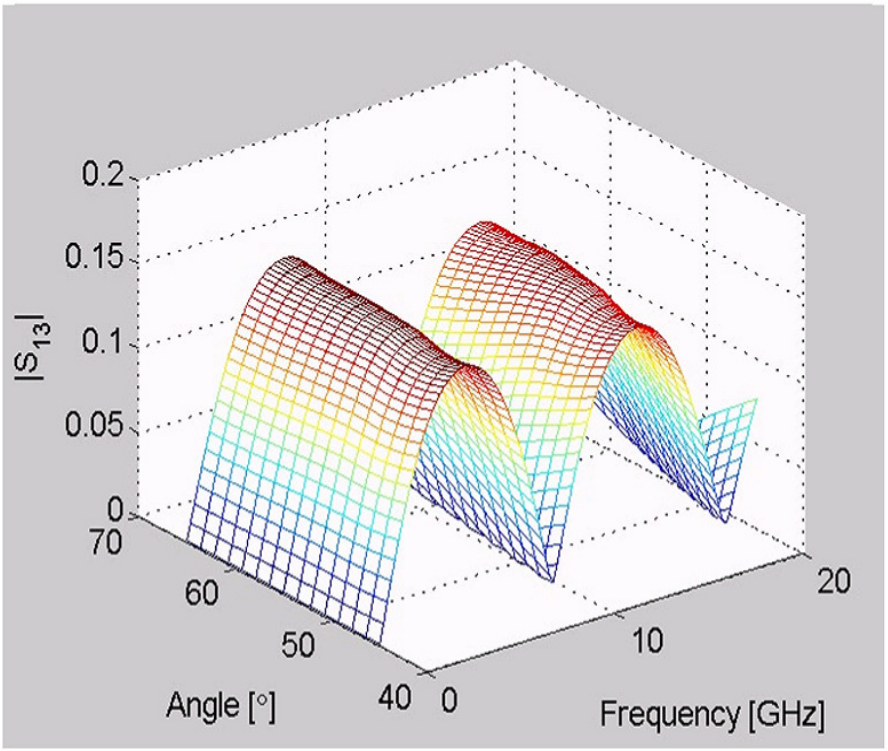
Data-driven PMOR example

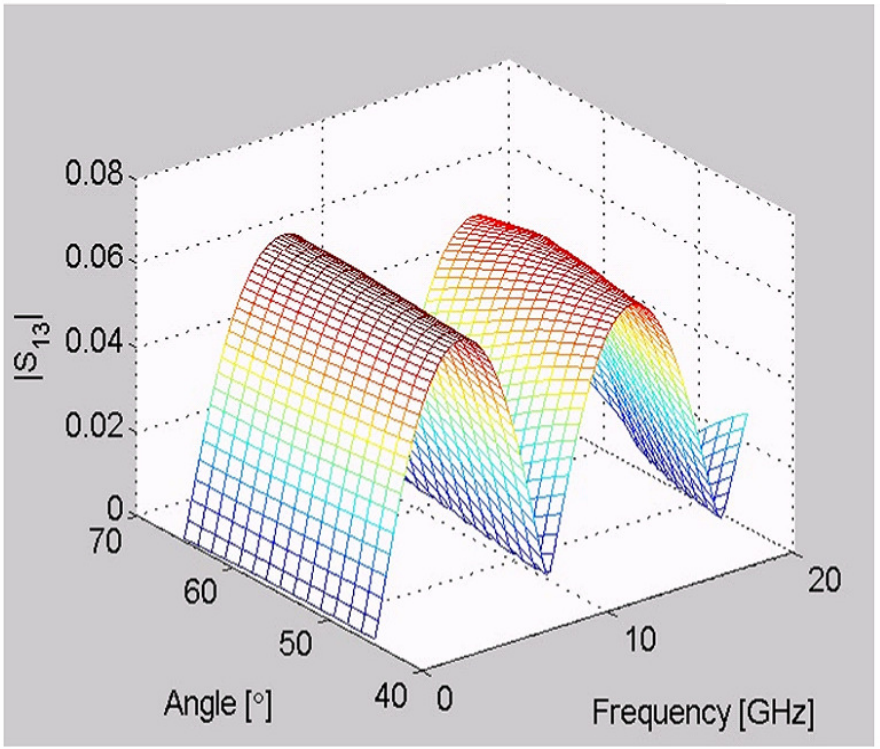
Poles



Data-driven PMOR example

Output





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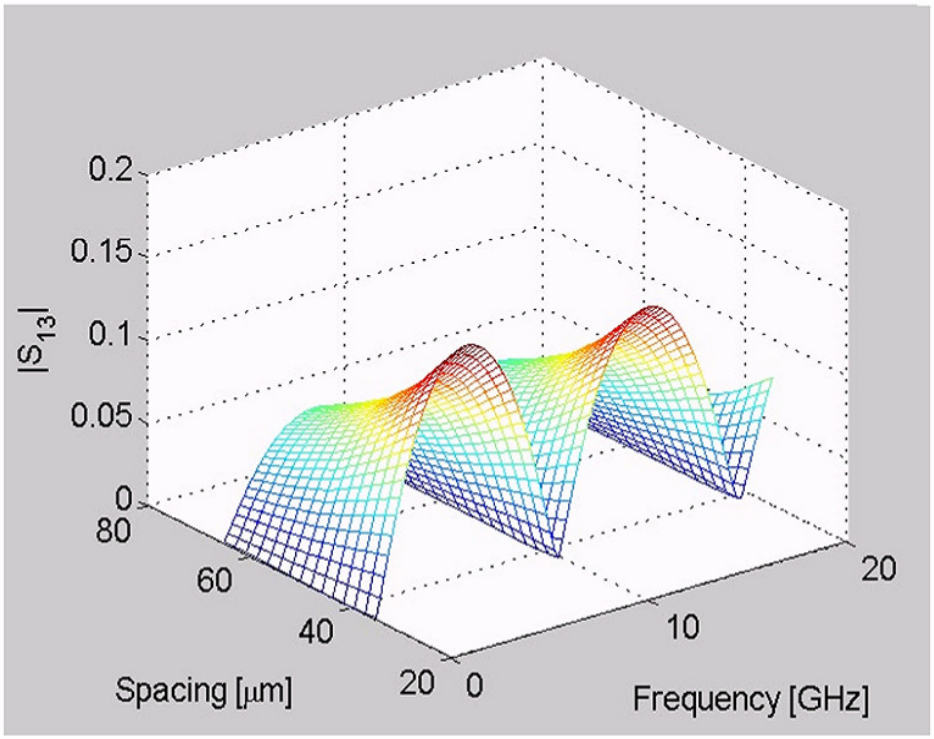
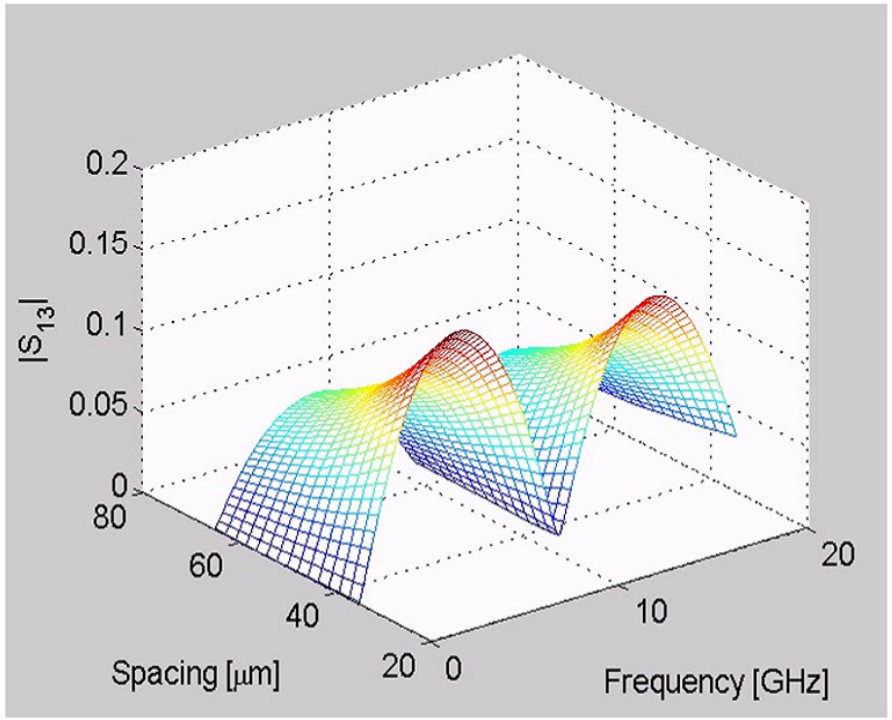
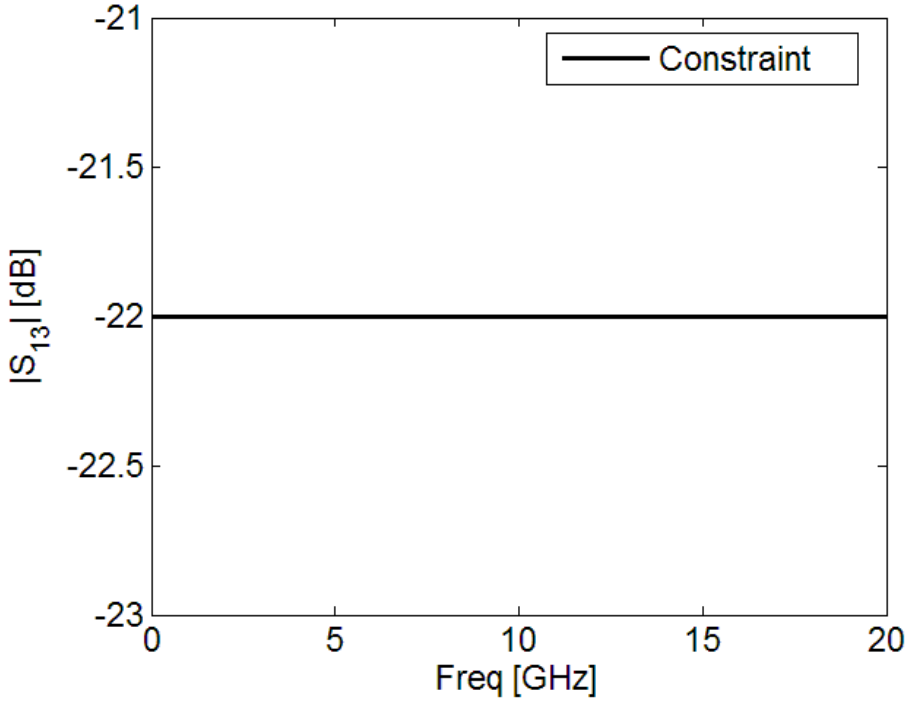




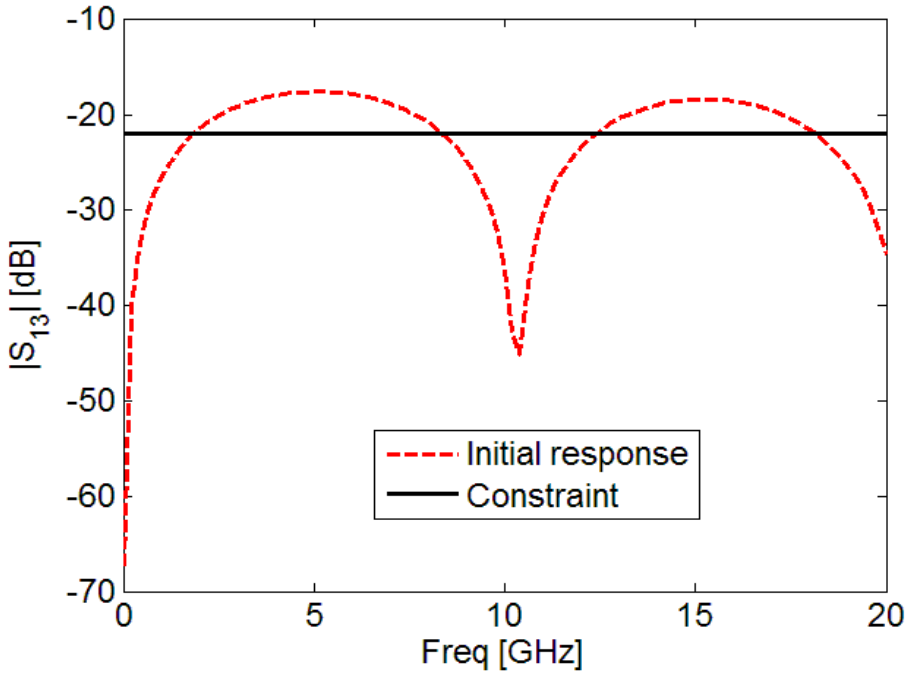
Data-driven PMOR example

- **Design optimization**
- **minimum S, minimum α**
- **$|S_{13}(s,S,\alpha)|$ <= -22 dB over [0 - 20] GHz**



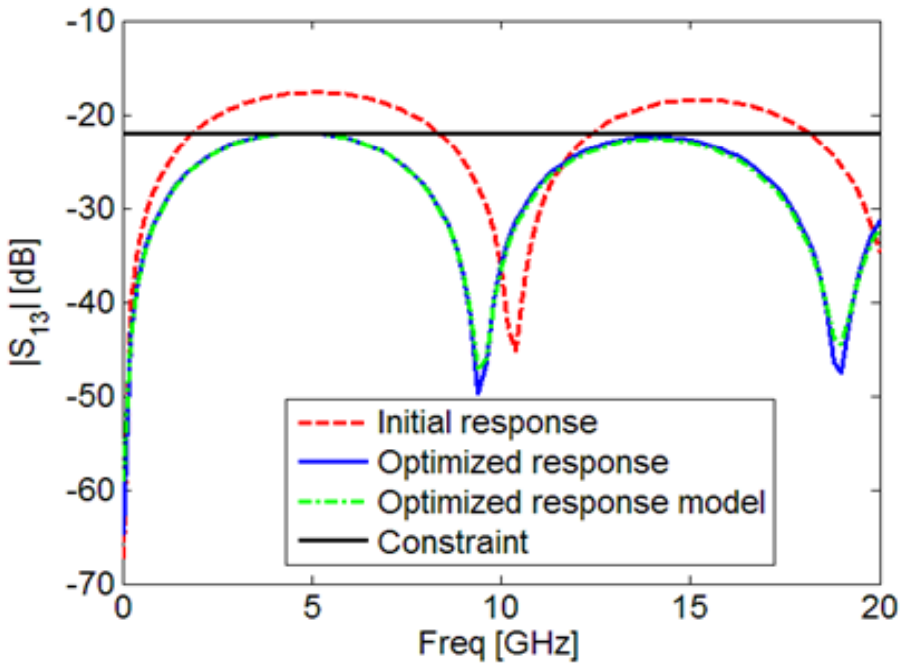
Data-driven PMOR example

- **Design optimization**
- **minimum S, minimum α**
- **$|S_{13}(s,S,\alpha)|$ <= -22 dB over [0 - 20] GHz**
- **initial values**



Data-driven PMOR example

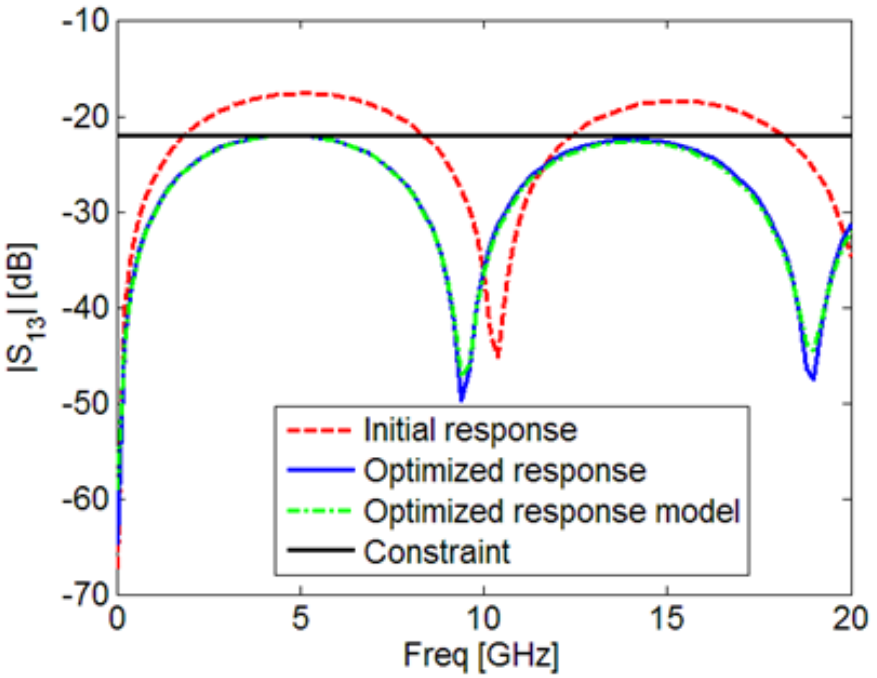
- **Design optimization**
- **minimum S, minimum α**
- **$|S_{13}(s,S,\alpha)|$ <= -22 dB over [0 - 20] GHz**
- **initial values**
- **optimal values**



Data-driven PMOR example

- **Design optimization**
- **minimum S, minimum α**
- **$|S_{13}(s,S,\alpha)|$ <= -22 dB over [0 - 20] GHz**
- **initial values**
- **optimal values**

Method	CPU time
EM solver	9 h
Parametric macromodel	37 s



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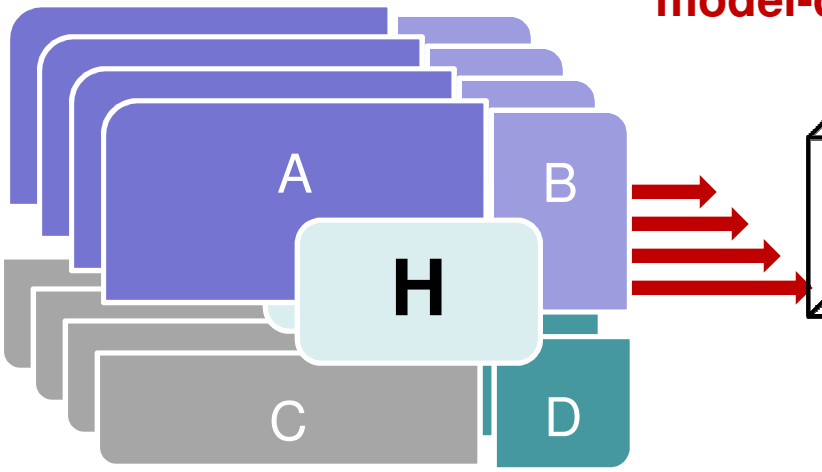
Numerical examples

- **Data-driven PMOR**
- **Model-driven PMOR**

Conclusions

Model-driven PMOR

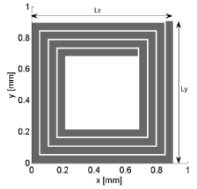
model-driven PMOR



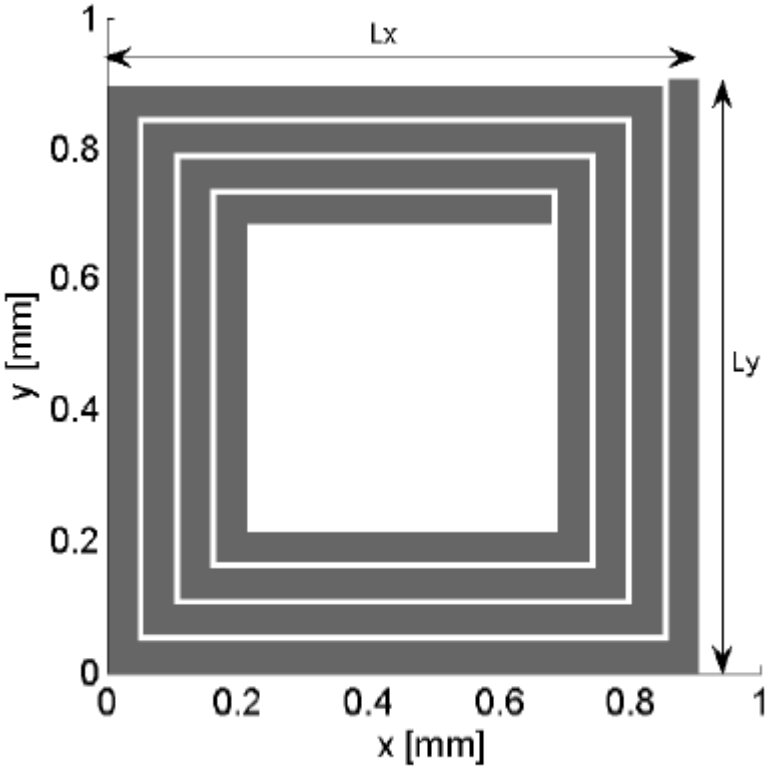
- accuracy
- efficiency
- stability guaranteed
- passivity guaranteed

Model-driven PMOR example

3D example: Spiral inductor



Parameter	Min	Max
Frequency ($freq$)	10 kHz	30 GHz
Horizontal length (L_x)	0.46 mm	0.93 mm
Vertical length (L_y)	0.46 mm	0.93 mm

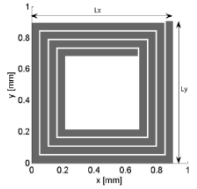


Original order = 801

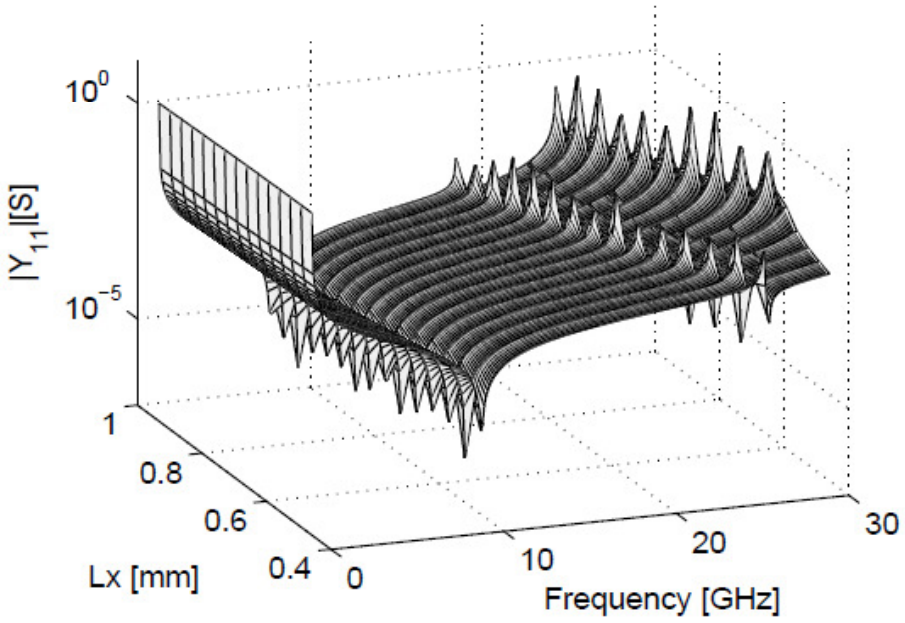
Reduced order = 91

Model-driven PMOR example

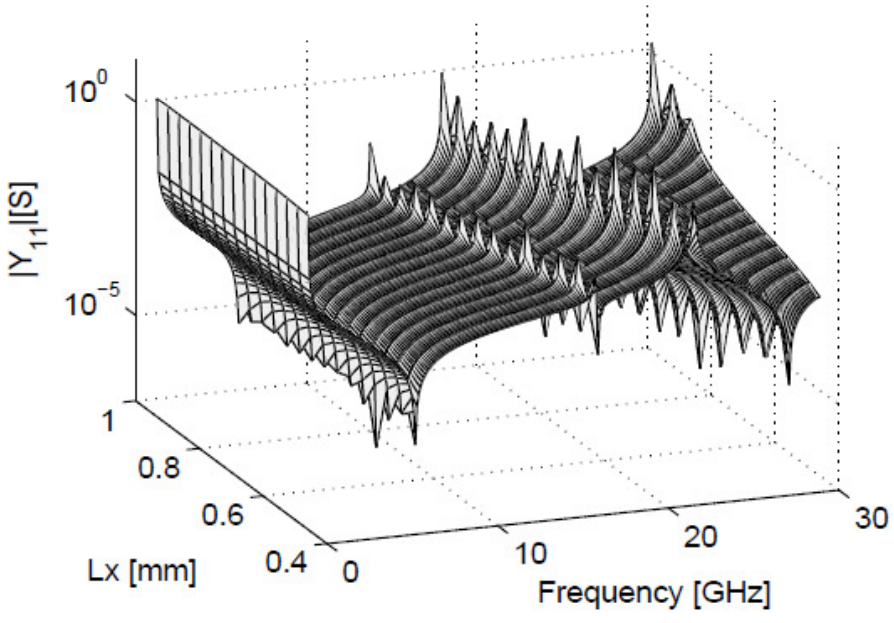
3D example: Spiral inductor



Ly= 0.46 mm

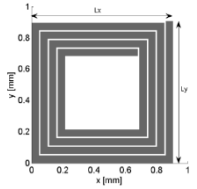


Ly= 0.93 mm

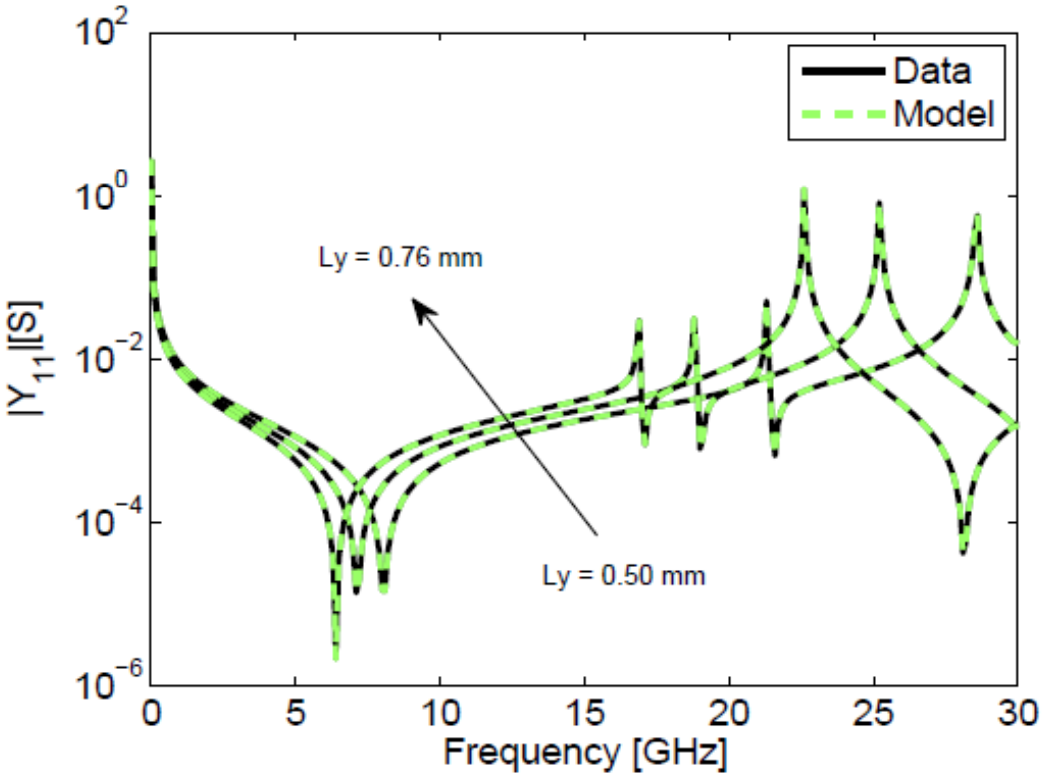


Model-driven PMOR example

3D example: Spiral inductor



Lx= 0.63 mm



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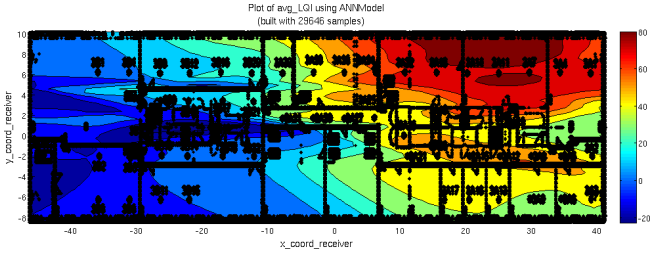
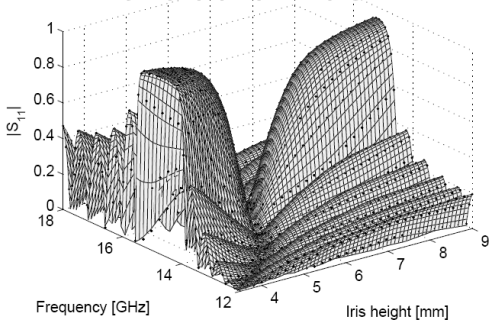
Conclusions

telecom

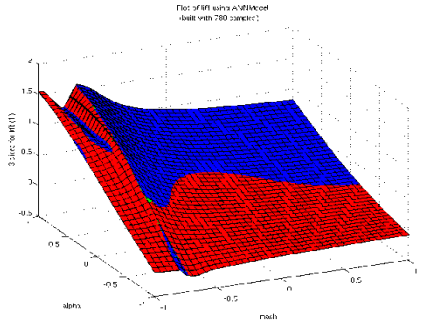


electronics



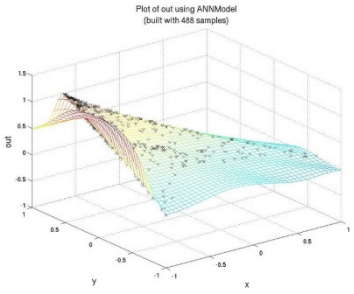
input → out = f(*in*) → output

fluid dynamics

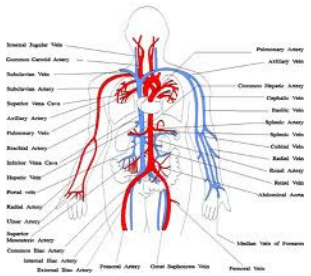


automotive

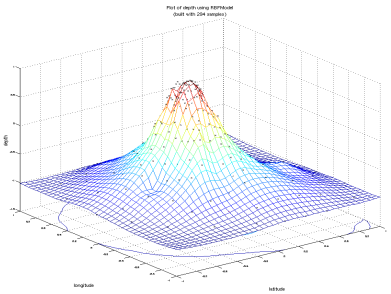
chemistry



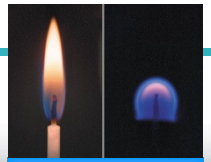
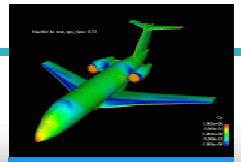
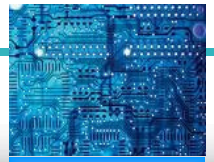
biomodeling



geology



Conclusions


Automotive | Chemistry | Aerodynamics | Electronics | Metallurgy

Design variables

width, temperature, angle, frequency, ...

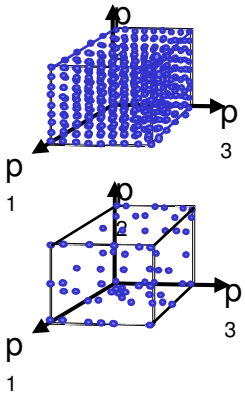
Simulation Model

Fluent®, HSPICE®, CST®, Comsol®, Abaqus®, ...

Costly

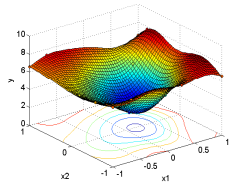
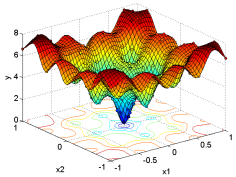
Response variables

lift, S-parameters, pressure, stress, ...



Configurable infrastructure

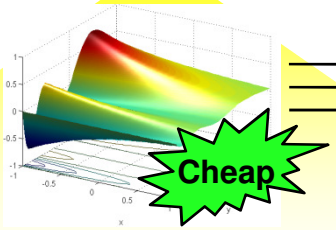
Adaptive Modeling

Distributed Computing

Design variables

Response variables



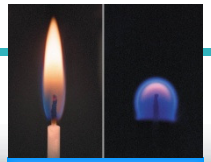
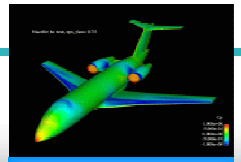
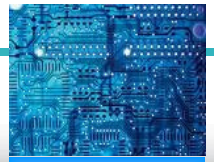
Cheap

Surrogate Model / Metamodel

Neural network, Kriging, SVM, rational function, spline,...

Prototyping | Optimization | Sensitivity Analysis | CAD/CAM/CAE Environment

Conclusions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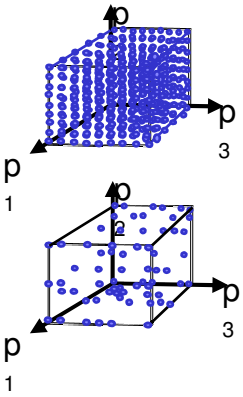

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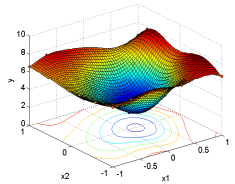
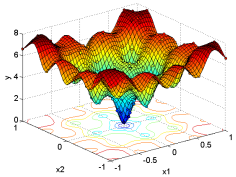

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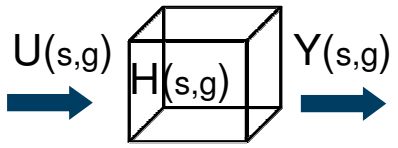
Scalable macromodels

Multiple design variables



scalable macromodel

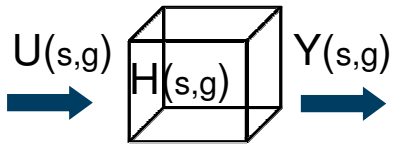
Compact models

Efficient design activities (excellent speed-ups)

- **Multiple simulations (measurements)**
  - **Design space optimization, exploration, sensitivity analysis**

Conclusions

Scalable macromodels



scalable macromodel

Time-domain simulations

- **Non-linear drivers and receivers**

Stochastic modeling

- **impact of manufacturing tolerances**

Models from measurements

- **noise to handle**

Applications in different domains

Questions